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Combined Statistical, Biological and-Categorical Models for Sensor Fusion

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James Bonick and Christopher Marshall

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The USA RDECOM CERDEC Night Vision and Electronic Sensors Directorate's Science and Technology Division investigated sensor fusion along three avenues: statistical, biological and categorical. The first two approaches are analyzed simultaneously to provide a precise and rigorous sensor fusion methodology. The statistical model currently enhances Bayesian methods for tracking, and suggests further application to target identification and fusion-involving both low level feature extraction and higher level sensor output combination. The biological model is also applied to multiple levels of the fusion problem. On the lowest level, it utilizes biologically-inspired results for improved feature extraction. On the higher levels, it develops biologically-inspired agency algorithms for sensor output combination and sensor network analysis. Ultimately, we model the entire fusion process with category theory. Category theory allows for the application of advanced mathematical theory to fusion analysis. In addition to using category theory as a modeling tool, in this paper we adapt categorical logic via topos theory to provide an advanced framework for decision fusion-initially using the topos of graphs.

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James Bonick and Christopher Marshall

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Science and Technology Division
FORT BELVOIR, VIRGINIA 22060-5806

CONTENTS

ABSTRACT

In this paper, we investigate sensor fusion along three avenues: statistical, biological and categorical. The first two approaches are analyzed simultaneously to provide a precise and rigorous sensor fusion methodology. The statistical model currently enhances Bayesian methods for tracking, and suggests further application to target identification and fusion—involving both low level feature extraction and higher level sensor output combination. The biological model is also applied to multiple levels of the fusion problem. On the lowest level, it utilizes biologically-inspired results for improved feature extraction. On the higher levels, it develops biologically-inspired agency algorithms for sensor output combination and sensor network analysis. Ultimately, we model the entire fusion process with category theory. Category theory allows for the application of advanced mathematical theory to fusion analysis. In addition to using category theory as a modeling tool, in this paper we adapt categorical logic via topos theory to provide an advanced framework for decision fusion—initially using the topos of graphs. Graphs are a simpler representation. We suggest formulations which will be much richer—toward the goal of a truly robust, reliable and computationally practical sensor fusion system for assisted/automatic target recognition.

1.0 Introduction

In this paper we attempt to develop a general model for sensor fusion—toward the goal of assisted/automatic target recognition (ATR). To accomplish this, we incorporate three strands into our plan. The first strand consists of methods based on biology. On the most primitive level, biological influence accounts for the basic choice of elementary feature extractors. On a higher level, biology inspires our study of agency for sensor networks. The second strand is statistical. Throughout our system, we plan to apply standard Bayesian methodology, particularly particle filters. Bayesian methods present an ideal way to approximate decisions in all levels of the fusion process "from the outside."

But we hope to push our model further. It is no secret that higher-level sensor fusion, ATR, and artificial intelligence in general have encountered significant difficulties over the last 40 years in truly and effectively modeling cognitive activity, as it occurs in individuals or in groups and networks. These difficulties can often be compensated for through vaster computational power—in effect, performing exhaustive searches over a representation space. But this solution can only be a temporary one. Increasingly, it has been accepted that there is a fundamental flaw in automated intelligent methods. We believe that that flaw stems from a lack of true subjectivity in machine learning. The question of whether that flaw can ever be overcome is unanswered, and an attempt to answer it is beyond the scope of this paper. However, our research aim is a methodology for optimally placing subjective elements in the system to address the flaw in artificial intelligence by "humans-in-the-loop." This concept is not novel, but we advance it here by attempting to develop a theory of human/computer and human/network interaction and a modeling technique that maximizes the effectiveness of the system by minimizing the human element to where it is essential, to develop a theory of assisted target recognition to supplant failed automatic target recognition. As will be shown in due course, we try to achieve these aims through category theory. In the following sections, we will first describe the individual elements that will make up our system, then describe the system and relate the broader implications of our approach to sensor fusion.

2.0 Biological and Statistical Methods

We adapt biological methods at both lower and higher levels. At the lower level, biologically based filters are used as feature extractors. For one-dimensional signals, wavelet analysis is appropriate. However, in two dimensions, wavelets may not be the best feature extractor. We utilize filters based on the human visual cortex. Our first approach utilized Gabor analysis. But for computational reasons, we abandoned this method in favor of oriented ridgelets. Ridgelets are, in effect, two-dimensional filters which are wavelets in one dimension. Figure 1 shows representations of Gabor and ridgelet filters.

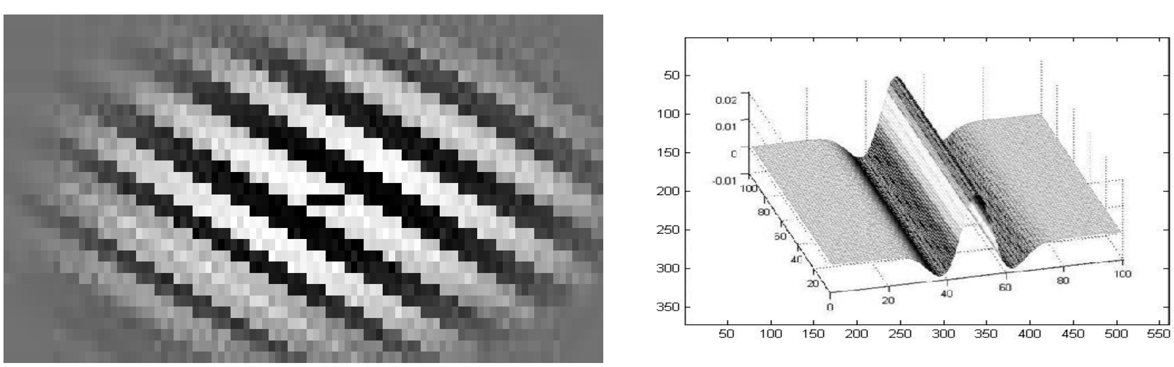

Figure 1. Sample Gabor filter (left) and Ridgelet filter (right).

At a higher level, we adapt biology to sensor fusion through the use of agents. Agents have been a very active topic in computer science for several years. They have also regularly been used to model sensor networks. "An *agent* is anything that can be viewed as *perceiving* its environment through *sensors* and *acting* upon that environment through *effectors*."[1] The preceding is a satisfactory definition, but in reality there is no official definition of agent in computer science. Additionally, an agent is not required to be a physical entity (for example, a robot). A section of software can be an agent. An agent's rationality is judged by how well it scores on some numerical performance measure. This is of course an external metric. An agent's perceptual history, the record of every datum it has perceived, is its percept sequence, and the agent's behavior is determined by a mapping or a function from the set of percept sequences to actions.

Computer agents lack an essential ingredient for real agency—subjectivity. Still, computer models can impersonate the inferential process of a real agent. This impersonation is usually referred to as machine learning or artificial or computational intelligence. The inference step is often handled with Bayesian or other statistical methods. Unfortunately, humans don't normally use Bayesian reasoning, although there is some evidence that if the problem is phrased in a form that brings out the Bayesian context, humans are more likely to reason in a Bayesian form. Very complicated group activity can be modeled by computer agents through achieving the outward appearance of inference and inductive reasoning in individual agents by careful mathematical processes. However, the learning and reasoning techniques for group agency are similar to the techniques used for individual agents. Figure 2 shows a rough diagram of our agency model, in 3 levels.

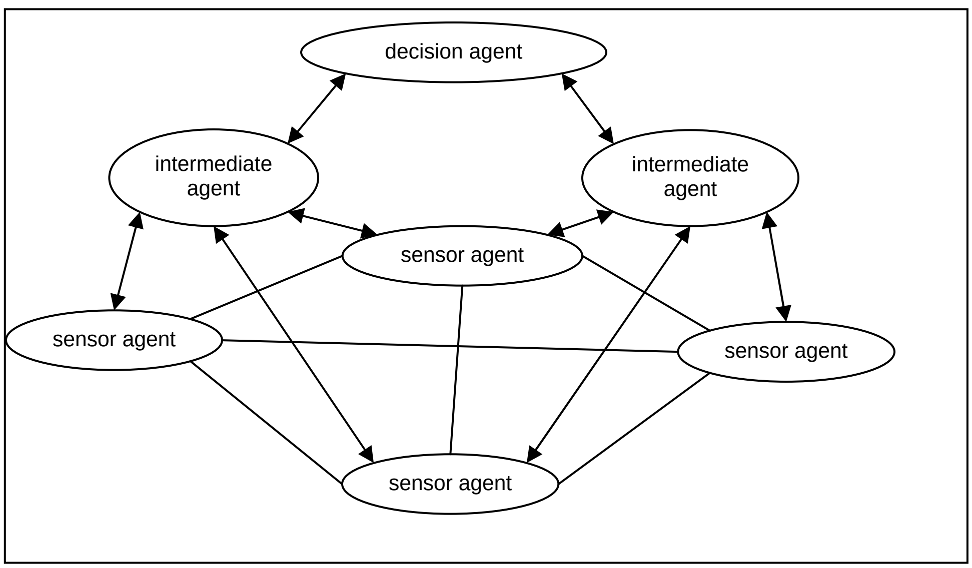

Figure 2. Sample agent diagram.

We have chosen particle filters as our prime statistical method, used in tracking. More generally, we will use Monte Carlo sampling generally for our statistical analysis as later we incorporate Bayesian classifiers into agents' classifying schemes. First in the tracking case, state x at time t is updated according to a function of x and a weight function of x. Observed state y is a function of the true state x and a noise function:

$$
\begin{aligned}
x_{t+1} &= f_t(x_t) + w_t(x_t) \\
y_t &= h_t(x_t) + v_t(x_t)
\end{aligned}
\qquad (1)
$$

The weights are updated at each time step by multiplying by the conditional probability of the observation y given the true state x. This probability is estimated usually by the distance between the particles that make up the probability density of x and the observation:

$$
\begin{aligned}
w_t^{(i)} &= w_{t-1}^{(i)} p(y_t \mid x_t^{(i)}) \\
p(x_t) &\approx \sum_{i=1}^{N} w_t^{(i)} \delta(x - x_t^{(i)})
\end{aligned} \tag{2}
$$

Also, the weights are normalized at each time step:

$$
w_t^{(i)} \leftarrow w_t^{(i)} / n \qquad n = \sum_{i=1}^{N} w_t^{(i)} \tag{3}
$$

Numerical classification is done via support vector machines (SVM). Support vector machines are not a statistical technique, but future work will involve including Bayesian classifiers (along with other classifiers) in the toolbox of agent classifiers. Solving a support vector machine consists of solving an optimization problem. Given a collection of labeled training data (x_i, y_i), $i=1,2,...,n$, $y_i \,\varepsilon\, \{+1,-1\}$, $x_i \,\varepsilon\, R^d$:

$$
\begin{gathered}
\text{minimize } \tfrac{1}{2}\|w\|^2 + C\Sigma\xi_i, \\
\text{subject to } y_i(w^T\phi(x_i)+b) \geq 1-\xi_i,\ \xi_i \geq 0,
\end{gathered} \tag{4}
$$

where ξ_i represent slack variables, C is an error penalization parameter, and w and b define a linear regressor in the feature space (the range space of the function ϕ). Support vector machine projects data into a higher dimensional space where linearly separation between the data is possible. Then the hyperplane $w^T\phi(x_i)+b=0$ is derived, maximizing the margin of separation. The hyperplane can be represented as:

$$
\Sigma\lambda_i y_i \phi(x_i)\cdot\phi(x)=0, \tag{5}
$$

where the λ_i are Lagrange multipliers. $\phi(x_i)\cdot\phi(x_j)$ is called the kernel function $K(x_i,x_j)$.

3.0 Categorical Methods

Category theory, higher category theory, and topos theory supply a suitable model for sensor networks.[2,3] Category theory views mathematical structures at a higher level of abstraction. Category theory is a way of doing mathematics emphasizing mappings more than objects, processes more than things. Its advantage over other modeling formalisms lies in its generality and extensive theory. Higher category theory expands category theory into higher dimensions, allowing higher levels of mappings. Topos theory was developed both through the application of category theory to logic and algebraic topology and algebraic geometry. We rely on Goldblatt for our descriptions of category theory and categorical logic.[4] A category is a collection of: 1) arrows; 2) objects; 3) assignments to each arrow a domain (object O_1) and a codomain (object O_2) (Figure 3); 4) a composition operation for arrows that is associative (Figure 4); and 5) an identity arrow (1_o) for each object (O) (Figure 3).

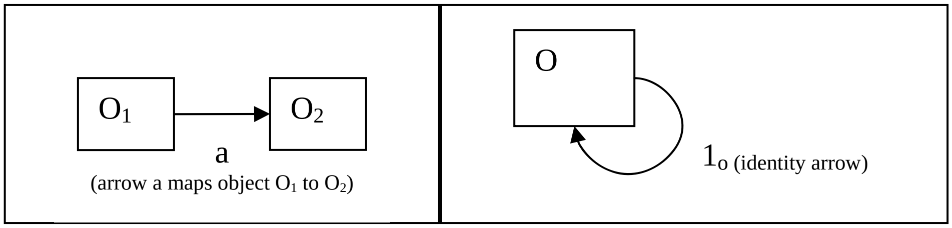

Figure 3. Diagram of domain and codomain (left), and identity arrow (right).

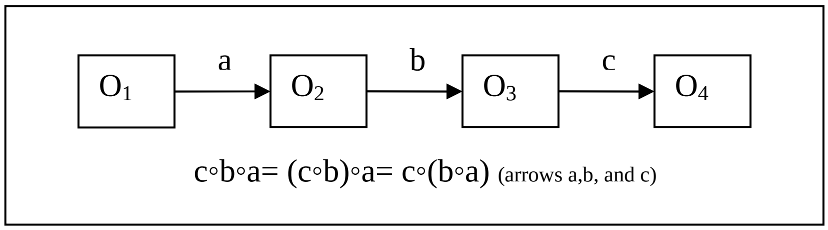

Figure 4. Diagram of associativity.

An object O in category C is initial (terminal) if there is only one arrow from (to) O to (from) every object in C. A product of objects X and Y is an object X×Y and arrows from X×Y to X and Y such that for any object Z with arrows to X and Y there is only one arrow from Z to X×Y such that the following diagram commutes—different paths of arrows from one object to another produce equivalent mappings. (See Figure 5).

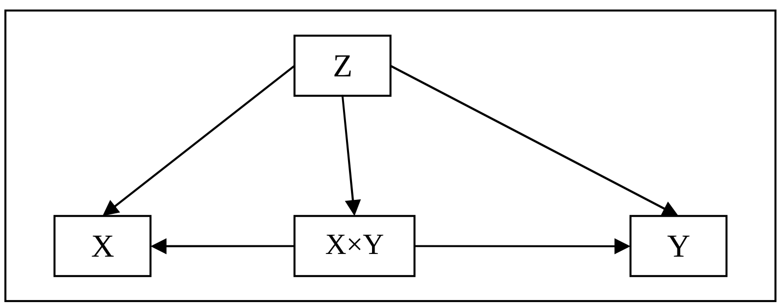

Figure 5. Diagram of product.

Given arrows a and b from object X to Y, an equalizer is an arrow e to X such that $a \circ e = b \circ e$ (Figure 6).

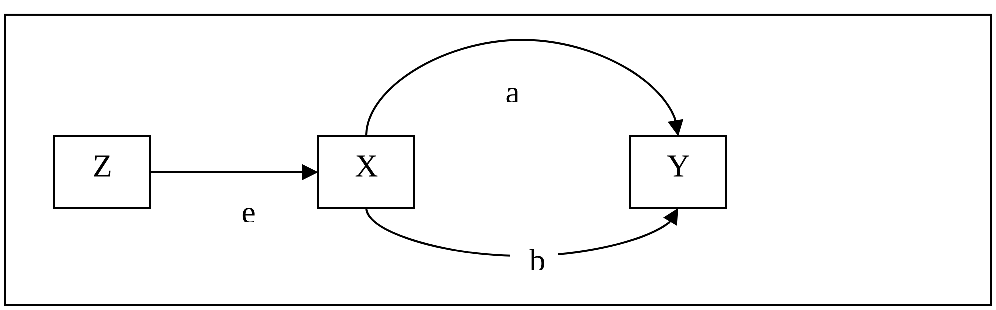

Figure 6. Diagram of equalizer.

A cone for a diagram is an object O and an arrow from O to each object in the diagram. O is a limit if for any other cone originating from object O', there is exactly one arrow from O' to O such that the following diagram (Figure 7) commutes.

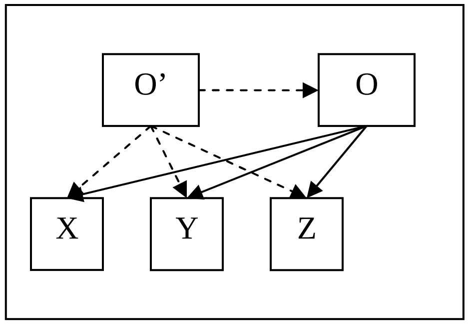

Figure 7. Diagram of a cone.

Category theory can be applied to logic. Classical propositional logic consists of sentences a, b, that are evaluated as

$$\text{TRUE}=1=\{\emptyset\} \quad (\emptyset \text{ is the null set; 1 is the set with the null set as its only element.}) \tag{6}$$

or

$$\text{FALSE}=0=\emptyset. \tag{7}$$

These sentences are combined with the following connectives: conjunction $a \cap b$, disjunction $a \cup b$, negation ~a, and implication =>. The truth values for new combined sentences are given by the standard truth tables. In an axiomatic system, truth is instead assigned to a collection of primary sentences called axioms. New true sentences can then be built up through deductive rules. In the category of sets, the set

$$2=\{0,1\}=\{\emptyset,\{\emptyset\}\}. \tag{8}$$

Conjunction is the characteristic function of $\{<1,1>\}$, a subset of 2X2. Negation is the characteristic function of

$$1=\{\emptyset\}, \tag{9}$$

a subset of 2. Implication is the characteristic function of

$$\leq=\{<0,0>,<0,1>,<1,1>\}, \tag{10}$$

a subset of 2X2. True is the map from $\{\emptyset\}$ to $\{\emptyset,\{\emptyset\}\}$ which takes 1 to 1,

$$\text{True}(1)=1. \tag{11}$$

False is the map from $\{\emptyset\}$ to $\{\emptyset,\{\emptyset\}\}$ which takes 1 to 0,

$$\text{False}(1)=0. \tag{12}$$

In order to include decision fusion in our system, we utilize topos theory. A topos is a category that has: 1) all finite limits; 2) exponentiation; 3) a subobject classifier. A category has all finite limits when all finite diagrams have a limit. Exponentiation and the subobject classifier can be illustrated through their set theoretical parallels. For set S, 2^S is the set of mappings from S to {0,1}. For any subset s of S, the standard characteristic function is equivalent to the mapping of 2^S which sends each element of s to 1 and each non-element to 0. Thus, 2 is the subobject classifier for the topos of sets. As will be shown, topos theory is a methodology for representing indeterminacy.[5] A functor is a mapping between categories that preserves structure. Objects map to objects. Arrows map to arrows. The identity arrows and arrow composition are preserved. A contravariant functor is a functor that reverses the direction of arrows. It maps domains to codomains and vice versa. A presheaf is a contravariant functor from a category to the category of sets. The category of presheaves over a category is a topos.

A higher dimensional category is a category whose objects are the arrows of a category C, and the arrows are mappings between them.[6] Figure 8 shows some examples of arrows in a 2-dimensional category. Higher categories can also have a chain of multiple arrows as a source (Figure 9). The process can be continued into higher dimensions (Figure 9).

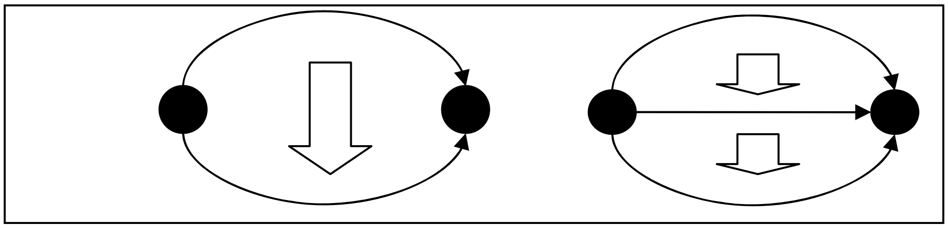

Figure 8. 2-Dimensional Categories.

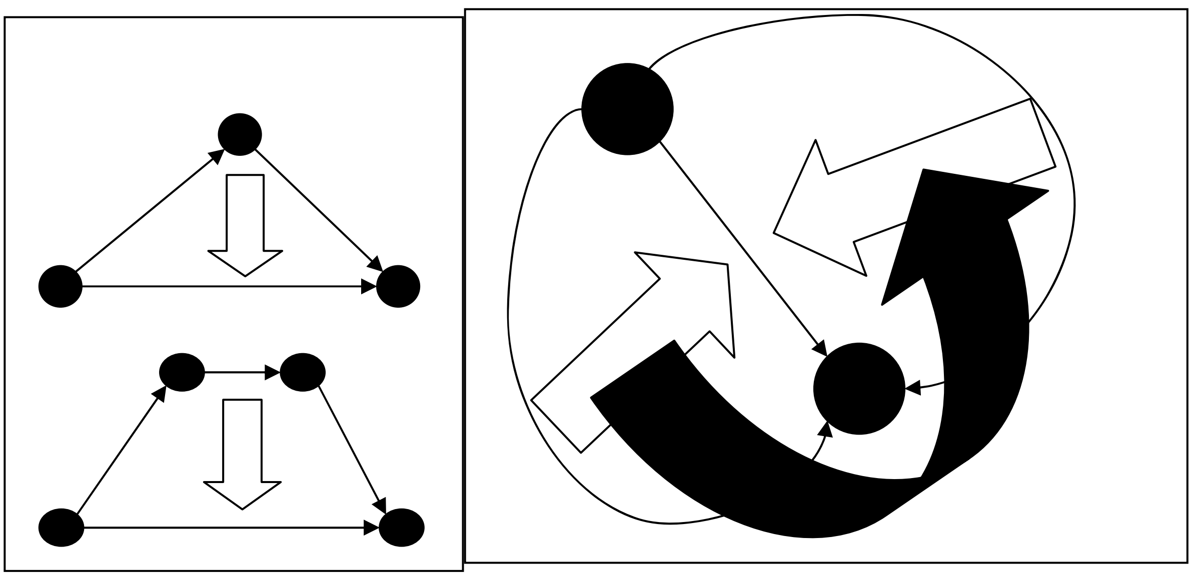

Figure 9. 2-dimensional category (left). In each case, the source is a sequence of arrows. 3-dimensional category (right). The black 3-dimensional arrow has as source and target, the white 2-dimensional arrows.

Category theory has been applied to modeling agents, although not sensor agents. Di Marzo et al. have described a formalization of multi-agent systems in category theory.[7] Although rudimentary, their ideas parallel some of our own, especially by suggesting topos theory as a model of indeterminacy. They describe categories of computational units, agents, services, and multi-agent systems. Functors are then defined between these categories. The robustness of category theory is that one can diagram one's system in a multitude of ways and then have access to advanced mathematical tools to manipulate it.

4.0 Putting it All Together

Our agent model is at this point straightforward. We intend to later add greater sophistication. Its current purpose is to provide a modeling framework within which to develop our categorical system. Agents types are: sensor agents (basic fixed sensors—currently low level image processing takes place within the sensor agent, although we intend to test adding functionality with a general image processing agent type);

classifying agents (mobile agents which visit the individual sensors, apply their respective classifying algorithms, and report to a higher level—currently the only differences between individual classifying agents are the parameters of their SVMs, but later we intend to include a vast diversity of classifiers); coordinating agents (these agents are assigned groups of sensors to monitor—they receive input from the classifying agents but can also access raw data from the sensor agents when necessary); and decision agents (these agents receive information from the coordinating agents, assign tasks to the coordinating agents, and report their decisions to the human monitor—currently tracking is done at this level, but we are experimenting with incorporating the tracking algorithm into other types of agents). The human monitor is the pinnacle of the system. He/she has access to all agent activity but generally deals with the decision agents while referring upon possible target identification to the sensor agents. The human monitor adds the vital element of subjectivity, making it a symbiotic subjective system. As an interesting aside, it could be possible with the success of the current research to supplant the human monitor with an animal in some situations. Figure 10 depicts a diagram the system.

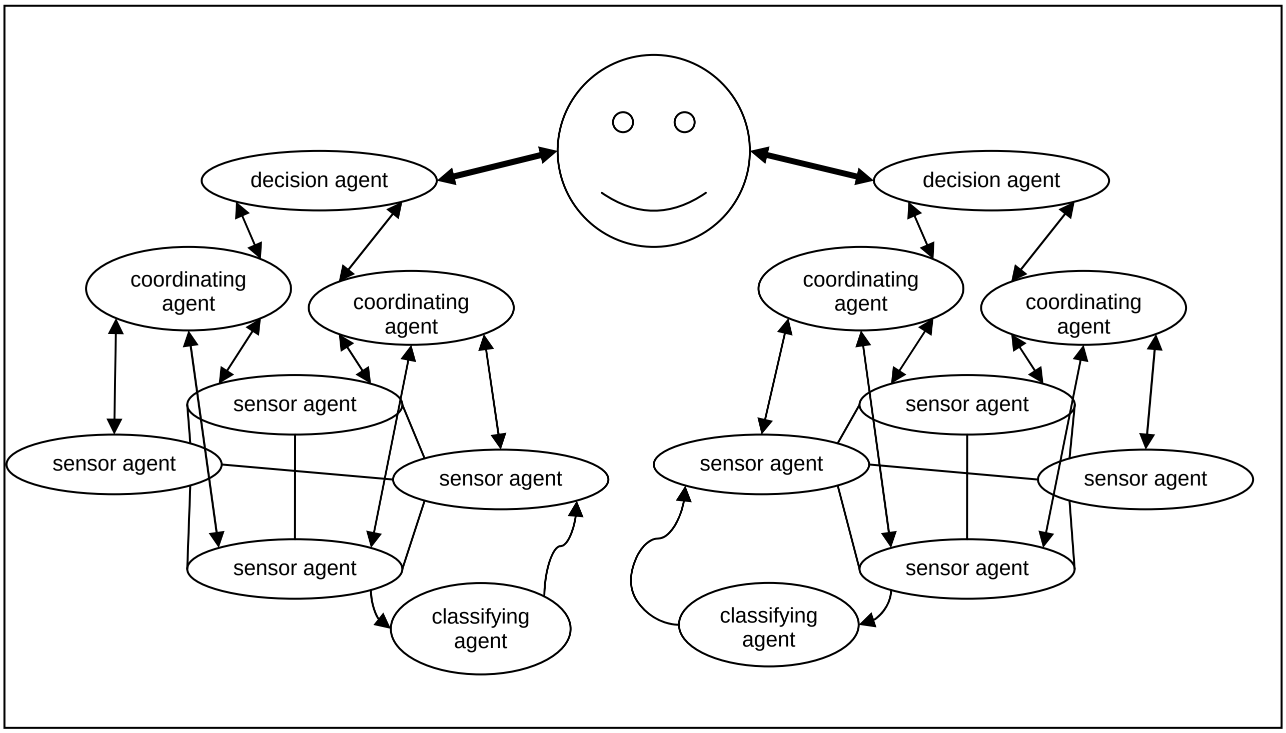

Figure 10. Diagram of the agent system. (figure at center represents “human in the loop.”)

Currently, agents interact through a simple blackboard system. Each agent has a multi-sheet spreadsheet file that it writes to. Agents gain information through accessing other agents’ files. So in fact, a mobile agent’s movement consists solely of reading successive files. A sensor-agent’s sensor input is written as a multi-dimensional matrix on the spreadsheet. Functions exist for manipulating data, reading spreadsheets, performing classifications, and fusing data and classifications. For the sensor agents, these functions include feature extraction with the biologically-based filters. Each agent is assigned a type, and each function’s input requires a specific type, but otherwise no protocol exists for restricting permission to access agent files. Of course, permissions will be added as the system evolves. Classifiers are presently strictly SVMs with various parameter formulations, although this too will be expanded to include Bayesian and other numerical classifiers—but also logical classifiers. The value of category theory is that it enables fusion of these disparate types of information.

We currently have defined two categories in our system. First, we have a category of agents, with subcategories for each agent type: classifying, sensor, coordinating, and decision. Each individual agent is an object of a category. The arrows are the functions between agents. Second, we have a process category, whose objects are the agent functions but also the image processing operations and the classifying and fusion operations—which correspond to an object with an arrow leading back to itself. These separate operations can be considered subcategories. With both agents and processes, it has not yet been fully determined to what degree we will work with the subcategories as separate categories or subsume them under the general categories. Note that the processes category is in fact, a 2-dimensional category.

Graph theory adapts well to the study of sensor networks. It also generalizes easily into category theory, with nodes in a directed graph corresponding to objects in a category and directed edges corresponding to arrows between the objects. We use the graph theoretical formulation of sensor networks. However, in order to apply topos theory, we work with the topos of graphs,[8] which is a presheaf topos. Here a topos consists of a base space, objects projecting on to the base space (individual directed graphs), and a subobject classifier. The base space is the category with objects (Nodes and Arcs) and arrows (Source and Target), $N^{s,t}\rightarrow A$, with a Source arrow from N to A if node N is the source of arc A and a Target arrow if node N is the target of arc A. Then any directed graph (object in the topos) is a projection onto the base space (Figure 11). For any subgraph of that graph, the subobject classifier determines membership in the subobject, in other words, the “truth” of membership in the subobject is not either/or. The logic of a presheaf topos is not necessarily Boolean. The law of the excluded middle might not apply. This is how topos theory models indeterminacy.

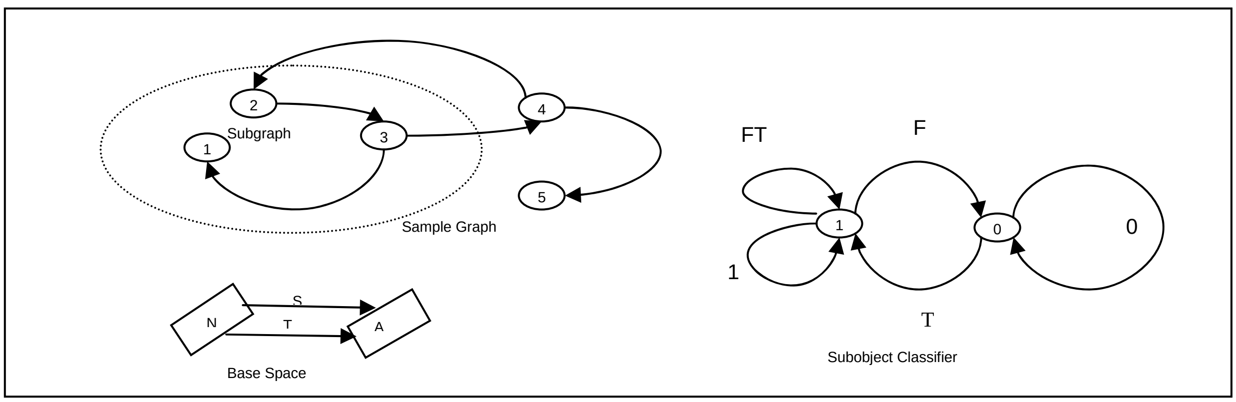

Figure 11. Sample graph over base space.

Note: Membership in the subgraph (enclosed by dotted line) is determined by mappings into the subobject classifier. Nodes inside the subobject map to Node 1 (true)—that outside map to Node 0 (false). Arcs map to various arcs of the subobject classifier depending on whether they are inside or outside (or neither) of the subobject.

This methodology can be applied to sensor fusion in two ways. The first begins with an individual sensor agent. Feature extractions are the presheaves, and the subobject classifier is the classifying agent, as illustrated in Figure 12. Another method would apply the theory to the entire sensor network, with presheaves identified as individual sensor network configurations over the sensor network base space. This second method is, in effect, applying higher category theory to the problem. Fusion is then modeled in our system by pullbacks (a type of product).[9]

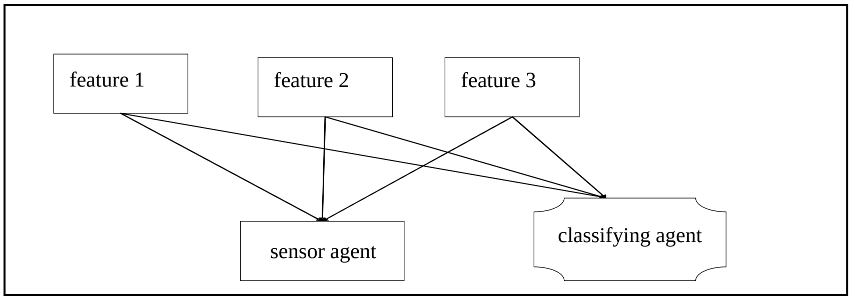

Figure 12. Simple Sensor Fusion Topos Model.

5.0 Conclusion

In this paper, we have devised a system, in fact a test bed, for representing sensor fusion and conducting sensor fusion experiments. We have adapted state of the art lower level fusion techniques and combined them with agent models and category theory. We are confident that agency within the category theory framework prove fruitful in amalgamating diverse sensors and sensor modalities—and both various numerical and logical classifiers. In addition, with topos theory we have shown a path toward effectively formalizing the decision process, and optimizing the placement of humans in the system—all toward creating a hybrid, subjective, sensor network.

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